2017

A Comparative Study on Using Meta-Heuristic Algorithms for Road Maintenance Planning: Insights from Field Study in a Developing Country

Ali Gerami Matin

Reza Vatani Nezafat
Old Dominion University

Amir Golroo

Repository Citation

Matin, Ali Gerami; Nezafat, Reza Vatani; and Golroo, Amir, "A Comparative Study on Using Meta-Heuristic Algorithms for Road Maintenance Planning: Insights from Field Study in a Developing Country" (2017). *Civil & Environmental Engineering Faculty Publications*. 17.
https://digitalcommons.odu.edu/cee_fac_pubs/17

Original Publication Citation

Gerami Matin, A., Vatani Nezafat, R., & Golroo, A. (2017). A comparative study on using meta-heuristic algorithms for road maintenance planning: Insights from field study in a developing country. *Journal of Traffic and Transportation Engineering*, 4(5), 477-486. doi:10.1016/j.jtte.2017.06.004

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/jtte

Original Research Paper

A comparative study on using meta-heuristic algorithms for road maintenance planning: Insights from field study in a developing country

Ali Gerami Matin [a,*], *Reza Vatani Nezafat* [b], *Amir Golroo* [c]

[a] *Department of Civil and Environmental Engineering, The George Washington University, Washington DC 20052, USA*

[b] *Transportation Research Institute, Old Dominion University, Norfolk, VA 23529, USA*

[c] *Department of Civil and Environmental Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran*

H I G H L I G H T S

- Proposed a meta-heuristic algorithm for the maintenance actions to maximize pavement performance and minimize maintenance cost.
- Single objective algorithms have failure in optimizing concurrently pavement performance and maintenance cost.
- Multi-objective algorithms performed better than the single objective algorithms.
- NSGAII algorithm performed better than MOPSO in terms of cost and pavement performance.

A R T I C L E I N F O

Article history:
Received 9 October 2016
Received in revised form
28 May 2017
Accepted 1 June 2017
Available online 18 September 2017

Keywords:
Meta-heuristic algorithms
Particle swarm optimization
Non-domination sorting genetic algorithm II
Multi-objective particle swarm optimization

A B S T R A C T

Optimized road maintenance planning seeks for solutions that can minimize the life-cycle cost of a road network and concurrently maximize pavement condition. Aiming at proposing an optimal set of road maintenance solutions, robust meta-heuristic algorithms are used in research. Two main optimization techniques are applied including single-objective and multi-objective optimization. Genetic algorithms (GA), particle swarm optimization (PSO), and combination of genetic algorithm and particle swarm optimization (GAPSO) as single-objective techniques are used, while the non-domination sorting genetic algorithm II (NSGAII) and multi-objective particle swarm optimization (MOPSO) which are sufficient for solving computationally complex large-size optimization problems as multi-objective techniques are applied and compared. A real case study from the rural transportation network of Iran is employed to illustrate the sufficiency of the optimum algorithm. The formulation of the optimization model is carried out in such a way that a cost-effective maintenance strategy is reached by preserving the performance level of the road network at a desirable level. So, the objective functions are pavement performance maximization and maintenance cost minimization. It is concluded that multi-objective algorithms including non-domination sorting genetic algorithm II (NSGAII) and multi-objective particle swarm optimization performed better than the single objective algorithms due to the

* *Corresponding author*. Tel.: +1 202 704 2228.
E-mail addresses: agerami@gwu.edu (A. Gerami Matin), agolroo@aut.ac.ir (A. Golroo).

Peer review under responsibility of Periodical Offices of Chang'an University.
http://dx.doi.org/10.1016/j.jtte.2017.06.004

capability to balance between both objectives. And between multi-objective algorithms the NSGAII provides the optimum solution for the road maintenance planning.

1. Introduction

Maintenance planning is a pronounced function of pavement management which involves a series of decisions on type, location, and time of maintenance actions that should be taken over the life span of the pavement in order to minimize the total maintenance cost and maximize pavement condition. So, the questions are which and when a segment should be maintained, and which maintenance action should be applied. Fig. 1 illustrates significance of executing maintenance actions on optimized preplanned time. The figure depicts the fact that if a maintenance action is not carried out on time, it might cost four times more in a short period of time afterwards.

Objective functions play a key role in providing an optimized maintenance plan. Various conflicting objectives have been applied to date such as minimum overall maintenance costs, maximum pavement condition or level-of-service, minimum safety hazards, maximum available resource utilization, and minimum disruption to traffic flows. Generally speaking, any maintenance policy planned with regard to only a single objective function may ignore or decline the importance of other objectives. For instance, a policy may minimize the total maintenance cost by sacrificing pavement condition or vice a versa. Multi-objective optimization is an appropriate tool to tackle such a problem through making a trade-off among different objective functions (Rose et al., 2010).

2. Background

Maintenance planning has been conventionally conducted employing single-objective optimization. The conventional single-objective optimization techniques such as linear programming, dynamic programming (Feighan et al., 1987) and integer programming (Fwa et al., 2000) have been widely utilized. Difficult modeling and formulation, and long computation time are the primary reasons that impose some limitations on using such models. This situation becomes inferior when multi-objectives are involved.

Different tools have been employed to perform optimization. Wang and Feng (1997) developed a network optimization model in order to maximize the pavement performance with the use of fuzzy systems. Ferreira et al. (2002a) developed a segment-linked optimization model called GENETIPAV-D using the genetic algorithm to reach the least discounted maintenance cost and rehabilitation strategy for various segments in a road network. In another study, the Ferreira et al. (2002b) applied a probabilistic approach to segment pavement link to carry out pavement management optimization. The probabilistic optimization planning approach has been also utilized by some researchers (Ferreira et al., 2002b; Abaza, 2005). This approach took advantage of a non-homogeneous discrete Markov chain to predict the future pavement conditions for a given pavement system. Kuhn (2010) deployed approximate dynamic programming in order to provide a maintenance plan for a large network of pavement. Jorge and Ferreira (2011) proposed a new maintenance optimization system called GENEPAV-HDM4 to integrate the pavement management system of the Municipality of Viseu, Portugal. Garza et al. (2011) developed a simpler and more useful network-level pavement maintenance optimization plan using the linear program method subjected to budget restrictions and the pavement performance thresholds. All the above-mentioned studies were conducted on the major roads. It seems that rural roads have not received enough attention by researchers. The multi-objective programming is a technique that can simultaneously satisfy more than one objective which may be more effective than a single-objective optimization model.

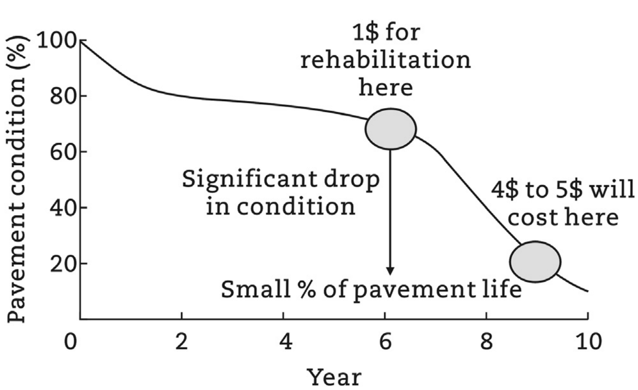


Fig. 1 – Pavement deterioration model.

3. Genetic algorithm

The genetic algorithm (GA) is a heuristic method that was first proposed by Holland which is inspired from the evolution of life in the real world (Holland, 1992) starting with randomly populating initial solutions. The solutions are evaluated and randomly mated based on their fitness using two operators called crossover and mutation. Then, offspring is produced as outcomes of mating process. The offspring is evaluated and replaced by the current solution with the lowest fitness. This procedure continues till the solutions converge or predetermined number of trials reach. The GA is an optimization tool for pavement maintenance programming which can be customized to accommodate requirements of multi-objective optimization problems. The GA takes advantage of solving probabilistic optimization problems (Chen and Chang, 1995; Liu et al., 1997; Yin, 2000; Herabat and Tangphaisankun, 2005). Although GA is one of the most efficient algorithms, it has two main drawbacks: (1) slow convergence and (2) weakness in the local search (Goldberg, 1989).

4. Particle swarm optimization

Another powerful algorithm to conquer complex continuous problems is the particle swarm optimization (PSO) developed by Eberhart and Kennedy (1995). It simulates the behavior of a swarm of particles moving to a potential well with an analogy to the birds flocking, fish schooling, or as an example bees swarming in search of pollen. The PSO starts with a random pool of particles/solutions. Each solution is identified by two vectors including velocity and position. The solution with the best vectors is selected and other solutions tend to be close to the best solution. Having fewer adjustable parameters is one of advantages of PSO over GA. It can often find nearly optimal solutions with an acceptable convergence speed but it has a weakness as well as the other algorithms. It usually fails to control its velocity step size for better tuning in search space, so it can easily end with an inappropriate convergence (Konak et al., 2006).

5. Genetic algorithm particle swarm optimization (GAPSO)

The combination of GA and PSO algorithms resulted in a new algorithm that has the advantages of both algorithms. It begins with initial random population and its evaluation with the PSO algorithm. The PSO algorithm is to optimize the whole population towards the best solution. The optimized population from PSO is utilized as initial population for GA. Afterwards, GA employs this optimized population for evaluation and mating procedures to obtain the best solution after reaching a predetermined convergence rate (Hegazy, 1999; Hegazy and Kassab, 2003).

6. Multi-objective particle swarm optimization (MOPSO)

In multi-objective particle swarm optimization (MOPSO) velocity position updates, the equations remain the same as basic equations of PSO. All the parameters declared are also the same, apart from the objective function. The typical approach is to use an external archive to store the leaders taken from the non-dominated particles in the swarm. After initialization of the leaders archive, some quality measures have to be calculated for all the leaders to select usually one leader for each particle of the swarm. In the main loop of the algorithm, the flight of each particle is performed after a leader has been selected and, optionally, a mutation or turbulence operator can be applied; then, the particle is evaluated and its corresponding measure is updated in the best way. After each iteration, the set of leaders is updated and the quality measure is calculated again. After the termination condition, the archive is returned as the result of the search (Coello and Lechuga, 2002; Elhadidy et al., 2015). The methodology of this algorithm is depicted in Fig. 2.

7. Non-domination sorting genetic algorithm II (NSGAII)

In the non-domination sorting genetic algorithm II, the population is ordinarily initialized. Once the population is initialized, it is sorted based on the non-domination into each front. A non-dominant member means that there is no other member in population which has better value than this member on both objectives. The first front is a completely non-dominant set in the current population and the second front is only dominated by the individuals in the first front

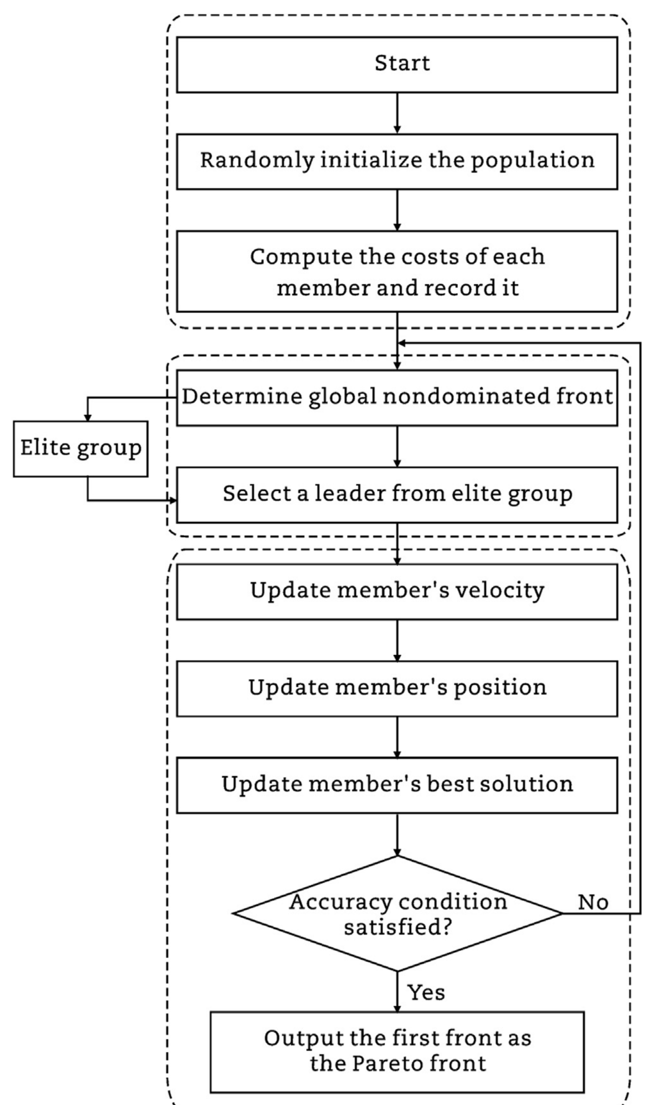


Fig. 2 — MOPSO algorithm.

and it goes on the same front until the last front is set of points which are dominated by all previous fronts. Each individual is assigned rank (fitness) values in each front based on the front which they belong to. Individuals in the first front are given a fitness value of 1 and a fitness value of 2 is assigned to the individuals in the second front and so on. In addition to the fitness value, a new parameter called crowding distance is calculated for each individual (Wei et al., 2009). A measure of how close an individual is to its neighbors is called the crowding distance. A better diversity in the population is reached by large average crowding distance. Taking advantage of the binary tournament selection based on the rank and crowding distance, parents are selected from the population. An individual is selected in the rank if it is lesser than the other or if crowding distance is greater than the other one. The selected population generates offspring from crossover and mutation operators. The population with the current population and the current offspring are sorted again based on the non-domination and only the best *N* individuals are selected, where *N* is the population size. The selection is based on the rank and crowding distance on the last front (Li et al., 2010; Ling et al., 2013). The procedure of the NSGAII is illuminated in Fig. 3.

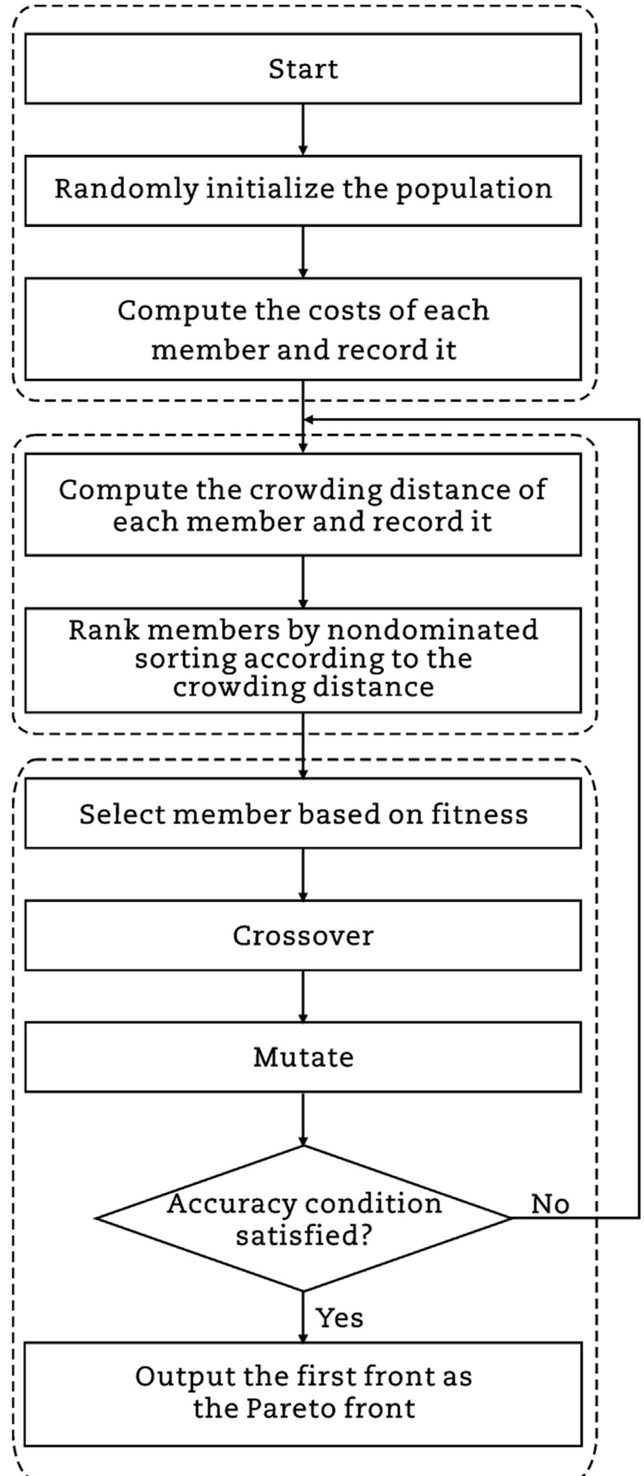


Fig. 3 – NSGAII algorithm.

8. Objective and research methodology

The main objective of this study is to develop an optimized road maintenance plan using the most effective meta-heuristic algorithm. For this purpose, several meta-heuristic algorithms are sufficiently studied and compared with each other resulting in indication of the optimum algorithm. A real case study from the rural transportation network of Iran is employed to illustrate the sufficiency of the optimum algorithm.

In order to compare the meta-heuristic algorithms, they are firstly divided into two major categories, single-objective and multi-objective. Then, some algorithms compatible with each category such as GA, PSO and some hybrid algorithms (GAPSO) are examined. Finally, the optimization models including performance and cost models are defined and solved using a real case study from rural road network of Iran to determine which algorithm is the best.

The formulation of the optimization model is carried out in such a way that a cost-effective maintenance strategy is reached by preserving the performance level of the road network at a desirable level. So, the objective functions are pavement performance maximization and maintenance cost minimization.

9. Maximization of pavement performance

To measure the performance of a road network, the Pavement Condition Index (PCI) was deployed as a well-developed and widely used index in all over the world. The problem presentation including both objective function and constraint definition are as follows.

$$\max\ Z_1 = \sum\nolimits_{s=1}^{S} \sum\nolimits_{t=1}^{T} \mathrm{PCI}_{st} \tag{1}$$

$$\min\ Z_2 = \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{k=1}^{K} X_{kst} C_k \frac{(1+r)^t}{(1+i)^t} \tag{2}$$

Subjected to

$$\sum_{s=1}^{S}\sum_{k=1}^{K}X_{kst}C_k \le B_t \quad 1<t<T \tag{3}$$

$$\sum_{k=1}^{K}X_{kst} \le 1 \tag{4}$$

$$\mathrm{PCI}_{st} > \mathrm{PCI}_{\min},\ 1 < t < T,\ 1 < s < S \tag{5}$$

$$40 < \mathrm{PCI}_{st} < 100 \tag{6}$$

$$X_{kst}\ [0, 1],\ 1 < t < T,\ 1 < s < S,\ 1 < k < K \tag{7}$$

where Z_1 and Z_2 refer to PCI and cost constraints, respectively. PCI_{st} and $\mathrm{PCI}_{s(t-1)}$ are the PCI values of the road section s in the network at time t and ($t-1$) year, respectively. X_{kst} is a binary decision variable which is 1 in the case of maintenance action k on section s at time t is executed, otherwise it takes 0. C_k is the cost of conducting the maintenance action k. i and r denote annual interest and inflation rates, respectively. B_t is the budget allocated to the tth year. There is often a severe limitation on the availability of annual budget for the maintenance of rural road networks. Eq. (3) ensures that the available budget allocated for each year should not be exceeded by the annual maintenance cost. As Eq. (5) shows, the maintenance actions should be conducted in such a way that the PCI of road sections should be above a minimum acceptable level. As shown in Eq. (6), maintenance treatments should also be carried out in such a way that the PCI does not exceed 100.

10. Performance model and maintenance cost

Pavement performance models express the degradation of pavement condition which can be represented by the PCI over time i.e., the trend of the PCI of sections at their different ages is depicted by a curve called a performance model. To develop such a model, one of the best approaches is to apply pavement condition historical data. In this study, a pavement performance model was developed based on the historical data as presented below

$$\mathrm{PCI}_t = -0.2496t^2 - 3.9451t + 95.11 \tag{8}$$

where PCI_t is PCI of a section at the end of time t, t is section age.

Maintenance and rehabilitation actions are divided into three categories including localized preventive, global preventive, and major maintenance. Localized preventive maintenance is defined as distress maintenance activities such as crack sealing and patching performed with the primary objective of slowing the rate of deterioration. Global preventive maintenance is defined as activities such as surface treatments applied to the entire pavement sections with the primary objective of slowing the rate of deterioration. Activities carried out on the entire pavement sections to correct or improve the existing structural or functional requirements which are defined as major maintenance. Major maintenance actions include reconstruction and structural overlays. It is assumed that the PCI value becomes 100 after the major maintenance. Table 1 represents the costs associated with different maintenance actions in the rural network based on the Iran national currency (IRR).

11. Improvement model

Implementing different maintenance activities may affect the condition of pavement in different ways resulting in variable levels of improvement of the PCI value. The improvement of PCI after conducting a maintenance action is described in Eq. (9).

$$\mathrm{PCI}_{st} = \mathrm{PCI}_{s(t-1)} + \sum_{k=1}^{K}X_{kst}\Delta\mathrm{PCI}_k \tag{9}$$

where $\Delta\mathrm{PCI}_k$ is an improvement in the PCI due to the action k.

The PCI of a section is improved whenever a maintenance action is performed. It is observed that the PCI improvement is highly dependent on the current PCI of a section. The PCI improvement of a rural road for a particular maintenance action has not received enough attention yet. Having conducted a maintenance action on a section, the deterioration mechanism is different from a new section. The pavement condition of a section should be evaluated after carrying out each maintenance action to compute PCI in order to model the actual improvement of the associated maintenance action.

In order to calculate the improvement rate, the Delphi technique was applied. This method employs the mean of expert opinion to come up with a variable which is looking for. Since the case study located in the rural road, no historical data in terms of maintenance actions was available. In other words, the improvement of pavement condition of a section after a treatment was not monitored and recorded. Therefore, the improvement rate cannot be measured using historical data. An alternative method deployed herein was expert knowledge. In this method, an effort was firstly made to classify the pavements in nine condition intervals based on PCI values. A questionnaire was designed and developed in order to ask experts to provide a number showing the improvement rate of pavement in a certain pavement condition interval based on a maintenance action. Based on the expert opinion, the average value of the improvements in PCI was calculated as presented in Table 2.

The effect of a maintenance action was accounted in terms of decrease in the age of pavement. For the sake of illustration, the procedure adopted to express the effect of maintenance treatment on the future performance of the pavement is shown in Fig. 4. This figure shows that the PCI of a road section at an age of 6 years is 62 and by conducting the global

Table 1 – Various maintenance actions estimated costs.

Estimated cost (IRR million/lane/km)	Various maintenance actions
15.90	Localized preventive
112.40	Global preventive
200.04	Major maintenance

Table 2 – PCI improvement for various maintenance actions on different pavement condition.

Description	PCI	Localized preventive	Global preventive	Major maintenance
Very good	>90	Not available	Not available	Not available
Good	80–90	2	10	10
Good	70–80	2	10	15
Fair	60–70	2	25	25
Fair	50–60	2	25	35
Fair	40–50	2	35	45
Poor	30–40	2	35	50
Poor	20–30	2	45	60
Very poor	<20	2	45	70

preventive maintenance action at this stage, its PCI will be increased by 25 units and will be 87. The effect of the maintenance on the road section is accounted as the reduction in the age of pavement. The adjusted age is taken as the age corresponding to a PCI of 87 which is 1.84 years. Taking this new age as the basis, the additional deterioration of the road section was calculated. When there was no treatment to be carried out, the pavement age was simply incremented and the deterioration was estimated as before. Using the same deterioration equation (i.e., Eq. (8)), the age of the road corresponding to the new PCI was back calculated by the trial and error process after each maintenance treatment. Therefore, whenever a treatment was carried out on a road section, its age has to be reset to an age corresponding to the improved PCI afterward and the additional deterioration was to be accounted from that age.

12. Case study

In this study, eight pavement sections were chosen. The area was located in the rural transportation network of the Khuzestan Province. The pavement condition data collection was conducted by the Ministry of Housing and Urban Soil Mechanics Laboratory. The PCI was carefully computed applying the acquired data and presented in Table 3.

13. Pareto front concept

The Pareto front concept is used to find a set of optimum solutions. There is another solution that is capable of enhancing, at least, one of the objectives without degradation of any other ones unless a solution belongs to the Pareto set (set of non-dominated solutions). Fig. 5 illuminates a schematic representation of the concept of Pareto-optimality considering two objectives. The region that represents all feasible solutions for all objective functions of the system is known as the feasible region. These solutions satisfy the system constraints, but the optimal solutions lie on the outermost lower-left edge of the feasible region (in the case of minimization). This set of Pareto-optimal solutions is generally called the Pareto front.

In multi-objective optimization taking advantage of Pareto front sorting, the fitness of a solution in a given iteration can be measured. The set of non-dominated solutions defining the Pareto front is identified and assigned a rank of one when the Pareto front sorting is used. These solutions are then set apart and a comparison is made among the remaining solutions in order to recognize a new set of non-dominated solutions with a rank of two. As shown in Fig. 5, this process will last until the entire population is ranked. A lower-numbered rank solution is assigned a higher fitness than that of a higher-numbered rank. This figure also illustrates the difference between the results of two algorithms, NSGAII and MOPSO. Generally speaking, MOPSO proposes slightly more cost-effective solutions, while NSGII suggests solutions with higher pavement quality. To take a deeper look at the figure, it is perceived that in most cases NSGAII has advantages over the MOPSO. In other words, at the same cost, NSGAII provides higher PCI values than MOPSO.

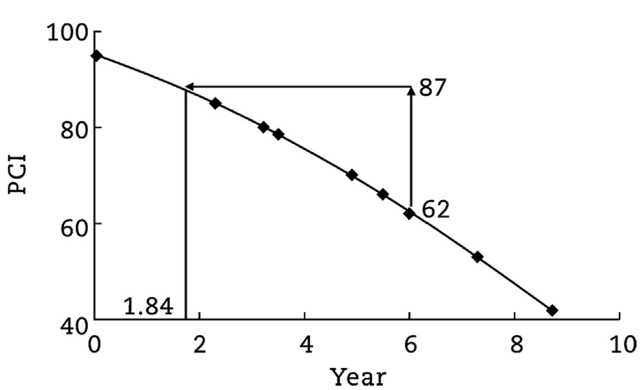


Fig. 4 – Improvement of PCI after performing a global preventative maintenance action.

14. Result and discussion

Comparing the results of GA, PSO, and GAPSO algorithms in Fig. 6, the PSO algorithm shows a significant difference in terms of high pavement quality comparing to other algorithms. However, it imposes significant cost on the system which causes it not to be an appropriate algorithm as shown in Fig. 7. Although the other two algorithms i.e., GA and GAPSO, need lower cost to implement maintenance actions in comparison to the PSO algorithm, they do not maintain the high pavement condition. It is worth mentioning that all algorithms meet the budget constraint expressed in Eq. (3). In other words, the PSO algorithm reaches higher PCI measures in the planning horizon of the pavement; however, it spends more money, less than the budget constraint, to maintain the PCI as high as possible.

Table 3 – Pavement condition details for the case study.

Road section ID	Pavement current age	Pavement current PCI
1	2.3	85
2	3.2	80
3	3.5	78
4	4.9	70
5	5.5	66
6	6.0	62
7	7.3	53
8	8.7	42

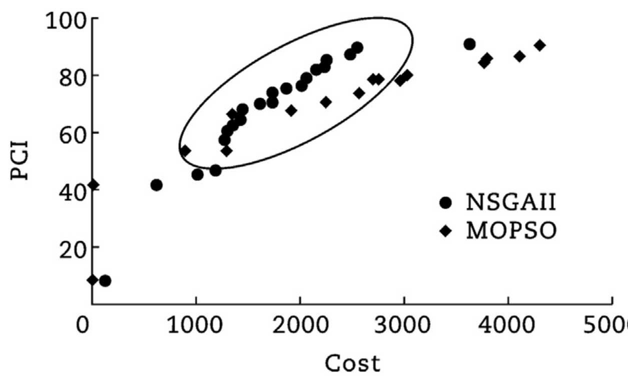


Fig. 5 – Pareto optimal solution.

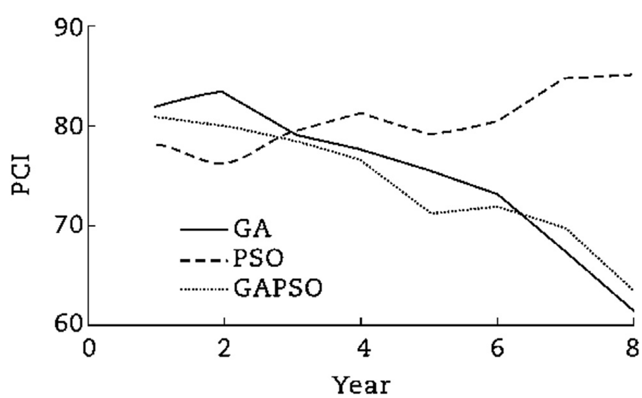


Fig. 6 – Single-objective algorithms performance comparison.

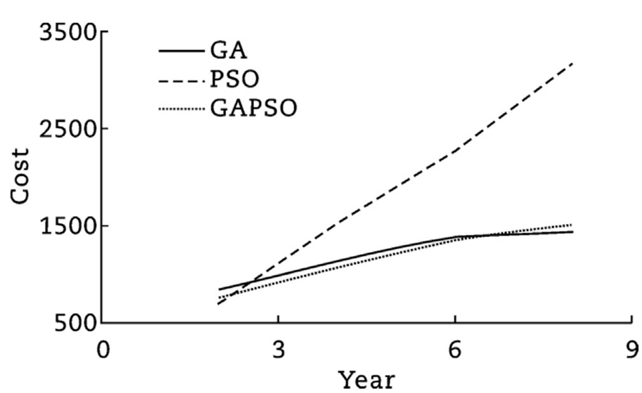


Fig. 7 – Single-objective algorithms cost (IRR) comparison.

The contradiction between cost and pavement quality is due to considering only one of them as a single objective function. However, a multi-objective algorithm can conquer this problem. The NSGAII and MOPSO were studied and applied herein as a multi-objective algorithm.

For better understanding the difference between single-objective Algorithms, an effectiveness index was introduced that was the total cost of maintenance actions divided by an average PCI of each method for the whole analysis period as illuminated in Fig. 8.

Figs. 9 and 10 show the pavement condition of some Pareto front solutions in NSGAII and MOPSO algorithms. These figures are almost similar in terms of final values of PCI showing the fact that these algorithms result in the same final values. Comparing these figures with Figs. 11 and 12, which compare the cost function at the same solutions, it is observed that the costs associated with the solutions are slightly different i.e., the MOPSO algorithm provides slightly more costly solutions as compared to those of NSGAII.

It was concluded that the NSGAII algorithm generally performs better than the MOPSO. Therefore, the NSGAII was applied on the case study. The GA settings were set-up at the condition when population is 45, iterations is 400, crossover is 0.75, mutation is 0.3. The final optimum solutions over the planning horizon of eight years are presented in Tables 4 and 5. Table 4 expresses the optimum maintenance actions that should be carried out in a specific year to come up with an

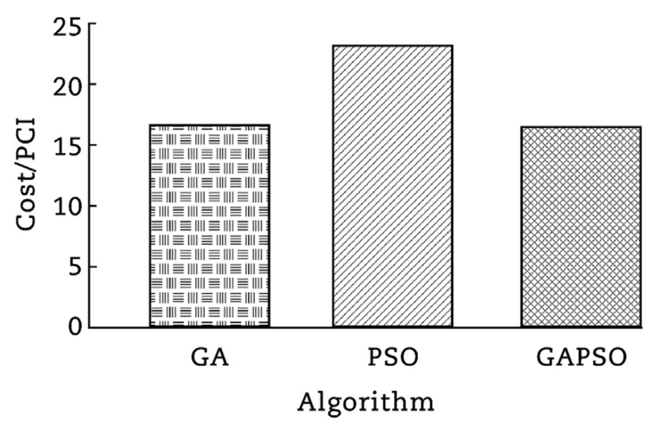


Fig. 8 – Single-objective algorithms cost/PCI comparison.

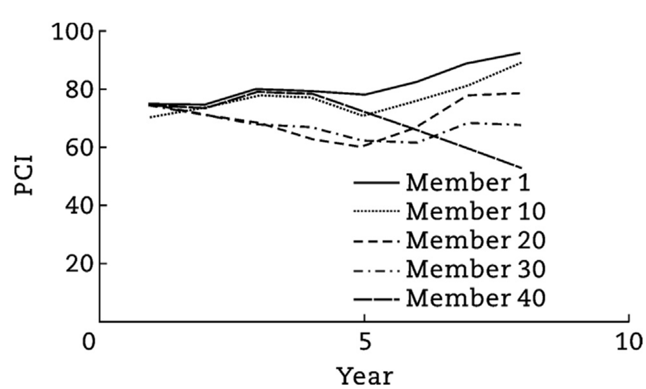


Fig. 9 – NSGAII Pareto front member performance.

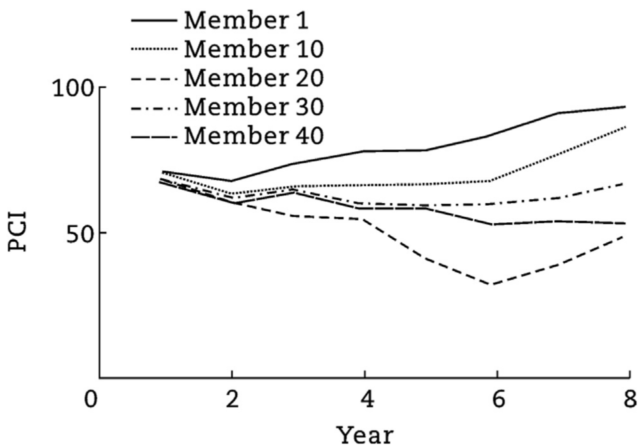


Fig. 10 – MOPSO Pareto front member performance.

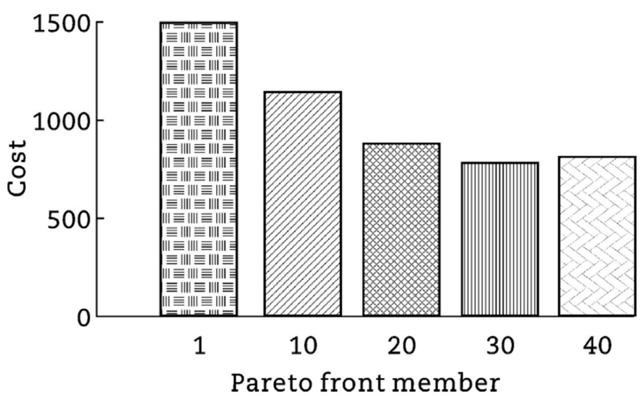


Fig. 11 – NSGAII Pareto front member cost (IRR).

overall optimum pavement condition and total costs. This table shows that mostly actions 0 and 1 are related to do nothing and localized maintenance as opposed to actions 2 and 3 that are related to global maintenance and major maintenance, respectively. This seems logical since actions 2 and 3 are more costly and improve the PCI more than the others, they should be applied less than the other maintenance actions. Table 5 also represents that

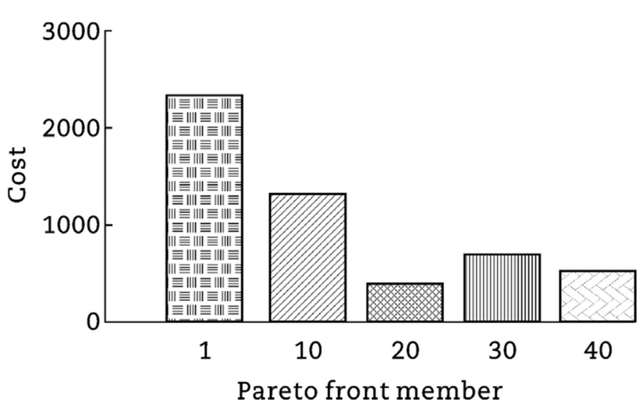


Fig. 12 – MOPSO Pareto front member cost (IRR).

Table 4 – A typical optimization of the case study maintenance actions by NSGAII algorithm (population is 45, iteration is 400, crossover is 0.75, mutation is 0.3).

Road ID	Year							
	1	2	3	4	5	6	7	8
1	0	0	0	0	0	0	0	0
2	0	0	0	1	0	2	2	3
3	0	0	0	0	0	0	2	0
4	0	0	0	0	3	0	0	0
5	1	2	2	0	0	0	0	1
6	0	0	0	0	0	2	0	0
7	0	0	1	2	0	0	0	0
8	0	0	0	0	0	0	0	0

Note: where 0 – do nothing; 1 – localized maintenance; 2 – global maintenance; 3 – major maintenance.

Table 5 – A typical optimization of the case study PCI by NSGAII algorithm (population is 45, iteration is 400, crossover is 0.75, mutation is 0.3).

Road ID	Year							
	1	2	3	4	5	6	7	8
1	85	80	78	70	66	62	53	42
2	81	75	72	77	62	77	71	73
3	79	69	64	72	56	74	90	70
4	72	61	56	66	80	69	86	65
5	78	76	72	61	75	61	81	81
6	73	71	66	54	71	78	76	76
7	69	66	71	71	64	72	70	71
8	64	60	67	66	57	68	65	66

pavement condition defined by PCI in each year over the same planning horizon. This table indicates that the minimum acceptable level of PCI which was assumed as 40 was met. The mean values of sections over eight years are more than almost 60 and the grand mean of the PCI is more than 66.

15. Conclusions

Road networks which play a vital role in the economy of each country require a comprehensive plan for the maintenance actions. Development of this plan is of a significant complexity mathematically speaking. The main aim of this study was to propose a meta-heuristic algorithm to tackle this problem that is to investigate the optimum maintenance plan for roads which satisfy two objectives including maximization of pavement performance and minimization of maintenance cost. The following findings were achieved.

- Single objective algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA) and the hybrid algorithm, i.e., genetic algorithm particle swarm optimization (GAPSO) did not performed sufficiently due to the failure in optimizing concurrently pavement performance and maintenance cost.

- Between single objective algorithms, PSO provided better pavement performance, while it imposed far more cost than the other algorithms to the system.
- Multi-objective algorithms including non-domination sorting genetic algorithm II (NSGAII) and multi-objective particle swarm optimization (MOPSO) performed better than the single objective algorithms due to the capability to balance between both objectives.
- The NSGAII algorithm generally performed better than the MOPSO according the optimum solutions offered in terms of cost and pavement performance.

REFERENCES

Abaza, A.K., 2005. An optimum stochastic model for pavement management. In: 84th Transportation Research Board Annual Meeting, Washington DC, 2005.

Chen, P.H., Chang, H.C., 1995. Large-scale economic dispatch by genetic algorithm. IEEE Transactions on Power Systems 10 (4), 1919–1926.

Coello, C.A.C., Lechuga, M.S., 2002. MOPSO: a proposal for multiple objective particle swarm optimization. In: 2002 Congress on Evolutionary Computation, CEC'02, Honolulu, 2002.

Eberhart, R., Kennedy, J., 1995. A new optimizer using particle swarm theory. In: Sixth International Symposium on Micro Machine and Human Science, Nagoya, 1995.

Elhadidy, A.A., Elbeltagi, E.E., Ammar, M.A., 2015. Optimum analysis of pavement maintenance using multi-objective genetic algorithms. HBRC Journal 11 (1), 107–113.

Feighan, K.J., Shahin, M.Y., Sinha, K.C., 1987. A dynamic programming approach to optimization for pavement management systems. In: 2nd North American Pavement Management Conference, Toronto, 1987.

Ferreira, A., Picado-Santos, L., Antunes, A., 2002a. A segment linked optimization model for deterministic pavement management systems. International Journal of Pavement Engineering 3 (2), 95–105.

Ferreira, A., Antunes, A., Picado-Santos, L., 2002b. Probabilistic segment linked pavement management optimization model. Journal of Transportation Engineering 128 (6), 568–577.

Fwa, T.F., Chan, W.T., Hoque, K.Z., 2000. Multiobjective optimization for pavement maintenance programming. Journal of Transportation Engineering 126 (5), 367–374.

Garza, J.M.D.L., Akyildiz, S., Bish, D.R., 2011. Development of network-level linear programming optimization for pavement maintenance programming. In: International Conference on Computing in Civil and Building Engineering, Nottingham, 2010.

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley Professional, Upper Saddle River.

Hegazy, T., 1999. Optimization of resource allocation and leveling using genetic algorithms. Journal of Construction Engineering and Management 125 (3), 167–175.

Hegazy, T., Kassab, M., 2003. Resource optimization using combined simulation and genetic algorithms. Journal of Construction Engineering and Management 129 (6), 698–705.

Herabat, P., Tangphaisankun, A., 2005. Multi-objective optimization model using constraint-based genetic algorithms for Thailand pavement management. Journal of the Eastern Asia Society for Transportation Studies 6, 1137–1152.

Holland, J.H., 1992. Adaptation in Natural and Artificial Systems. An Introductory Analysis with Application to Biology, Control, and Artificial Intelligence. The MIT Press, Cambridge.

Jorge, D., Ferreira, A., 2011. Road network pavement maintenance optimization using the HDM-4 pavement performance prediction models. International Journal of Pavement Engineering 13 (1), 39–51.

Konak, A., Coit, D.W., Smith, A.E., 2006. Multi-objective optimization using genetic algorithms: a tutorial. Reliability Engineering and System Safety 91 (9), 992–1007.

Kuhn, K., 2010. Pavement network maintenance optimization considering multidimensional condition data. Journal of Infrastructure System 18 (4), 270–277.

Li, Z., Li, Y., Duan, X., 2010. Non-dominated sorting genetic algorithm-II for robust multi-objective optimal reactive power dispatch. Generation, Transmission & Distribution 4 (9), 1000–1008.

Ling, J.M., Du, Z.M., Yuan, J., 2013. Optimum maintenance and rehabilitation decision making considering delay effects for airport pavement management. International Journal of Pavement Research and Technology 6 (5), 602–611.

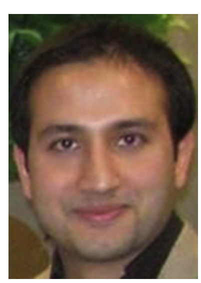
Liu, C., Hammed, A., Itoh, Y., 1997. Maintenance strategy optimization of bridge decks using genetic algorithm. Journal of Transportation Engineering 123 (2), 91–100.

Rose, S., Mathew, B.S., Isaac, K.P., et al., 2010. Pavement performance modeling and calibration of HDM-4 deterioration models for rural roads in India. Journal of Institution of Engineers 91, 29–35.

Wang, D., Feng, X.D., 1997. Synthesis of poly (glycolic acid-alt-L-aspartic acid) from a morpholine-2, 5-dione derivative. Macromolecules 30 (19), 5688–5692.

Wei, J.J., Kong, Y.J., Fu, Z., 2009. Multi-objective optimization for pavement maintenance and rehabilitation strategies. In: International Conference on Transportation Engineering 2009, pp. 2919–2924.

Yin, Y.F., 2000. Genetic-algorithms-based approach for bilevel programming models. Journal of Transportation Engineering 126 (2), 115–120.



Dr. Amir Golroo has extensive hands-on industrial experience. The most recent one is with analysis of automated and semi-automated data collected of road networks in Fugro Roadware Inc. He has strong background in research experience in the field of transportation engineering. Dr. Golroo accomplished his B.Sc. in civil engineering at University of Amirkabir and graduated with M.Sc. in transportation planning from Iran University of Science & Technology. His previous study comprised investment prioritization of transport networks in a disaster manner. Dr. Golroo experienced working as a PhD student with Prof. Alan Nicholson and Andre Dantas at the University of Christchurch, New Zealand in the transportation group. Dr. Golroo has completed his PhD at the University of Waterloo, Canada in the transportation group.

His research interests are pavement engineering, modeling, and management, development and evaluation of infrastructure management system, application of soft-computing tools in pavement management, sustainable long life infrastructure, application of asset management to highway and road network, designing and building environmentally friendly roads, life cycle economic analysis as a tool for infrastructure management and evaluating new types of pavement. His most recent research is in the area of pervious concrete pavement management including producing a guideline for distress evaluation of pervious concrete pavement, developing a novel combined condition index for

pervious concrete pavement, and modeling, validation, and calibration of performance models for pervious concrete pavement. He has received several research and academic awards (e.g., CTRF first prize in the PhD category and UW graduate scholarships). He has over 30 publications, licensed as Professional Engineers of Ontario (PEO), and serves on a number of professional committees as a reviewer such as the Pavement Management Systems Committee (AFD).

Dr. Golroo has been an assistant professor at the Amirkabir University of Technology, Civil and Environmental Engineering Department since January 2012. He is the director of scientific and international cooperation of Amirkabir University of Technology.